

Lecture 7 Fast Johnson-Lindenstrauss

Let's fix a set $U \subseteq \mathbb{R}^d$ of m points. JL tells us that a Gaussian matrix $X \in \mathbb{R}^{n \times d}$ satisfies

$$1 - \varepsilon \leq \frac{\|Xu - Xv\|_2}{\|u - v\|_2} \leq 1 + \varepsilon \quad \text{forall } u, v \in U$$

with probability $1 - \delta$, as long as

$$n = \Omega\left(\frac{\log\left(\frac{m}{\delta}\right)}{\varepsilon^2}\right)$$

The cost of forming Xu is $O(dn)$ flops.

We will prove that there exists a matrix $L \in \mathbb{R}^{n \times d}$ that satisfies the conclusions of JL but forming Lu costs $O(d \log(d) + n \log(d/m))$ flops.

First attempt: Let's try to construct a super sparse matrix with a single nonzero entry per row.

For each i , let

$$L_i = \sqrt{\frac{d}{n}} e_j \text{ w.p. } \frac{1}{d}$$

E.g.:

$$h \underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}}_d$$

Let's check the norm in expectation:

$$\begin{aligned}\mathbb{E} \|Lu\|_2^2 &= \sum_i \mathbb{E}(L_i u)^2 \\ &= \sum_i \sum_j \frac{d}{n} \cdot u_j^2 \cdot \frac{1}{d} \\ &= \frac{1}{n} \sum_i \sum_j u_j^2 = \|u\|_2^2\end{aligned}$$

So $\|Lu\|_2^2$ has the right mean, but does not concentrate well for example when $u = e_1$. Indeed

$L e_1 = 0$ with probability

$$p = \left(\frac{d-1}{d}\right)^n = \left(1 - \frac{1}{d}\right)^n$$

So $\log(p) = n \log\left(1 - \frac{1}{d}\right) = \frac{n}{d} + o\left(\frac{1}{d}\right)$

So need $n \approx d$ to have $p < \frac{1}{2}$ for example.

On the other hand if u is not aligned with the axes L_u does concentrate well.

Lemma: Let $u \in \mathbb{R}^d$ be such that

$$\|u\|_\infty^2 \leq \lambda \cdot \|u\|_2^2$$

Then $P[|\|L_u\|_2^2 - \|u\|_2^2| \geq \epsilon \|u\|_2^2] \leq 2 \exp\left(-\frac{\epsilon^2 n}{d^2 \lambda^2}\right)$

Pf: Observe $\|L_u\|_2^2 = \sum_i (L_i \cdot u)^2$

and $(L_i \cdot u)^2 = \frac{d}{n} u_j^2$ w.p. $\frac{1}{d}$

Therefore $(L_i \cdot u)^2$ is $\frac{d \|u\|_\infty^2}{2n}$ -subGaussian

Hoeffding implies $\|L_u\|_2^2$ is $\frac{d \|u\|_\infty^2}{2\sqrt{n}}$ -subGaussian and therefore

$$P[|\|L_u\|_2^2 - \|u\|_2^2| \geq \epsilon \|u\|_2^2]$$

$$\leq 2 \exp\left(-\frac{\epsilon^2 \|u\|_2^4 n}{d^2 \|u\|_\infty^4}\right) \leq 2 \exp\left(-\frac{\epsilon^2 n}{d^2 \lambda^2}\right)$$

Idea: Apply first a random matrix R to u_i so that Ru_i is not aligned with coordinate axes. Specifically we would like

Incoherence ✓

$$\|Ru_i\|_\infty \approx \frac{1}{\sqrt{d}} \|Ru_i\|_2$$

in order to apply the lemma.

But R should be such that Ru is easy to compute.

Defn: A Hadamard matrix $H \in \mathbb{R}^{d \times d}$ is one that is orthogonal and has all entries in $\left\{-\frac{1}{\sqrt{d}}, \frac{1}{\sqrt{d}}\right\}$

Ex: For $d=2$, have

$$H_2 = \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \end{bmatrix}$$

~ 45° degree rotation

For powers $d = 2^k$ we may set

$$H_d = \begin{bmatrix} H_{d/2} & H_{d/2} \\ H_{d/2} & -H_{d/2} \end{bmatrix} / \sqrt{2}$$

Lemma: H_d is Hadamard.

Pf: By induction $H_d(i,j) = \pm \frac{\sqrt{2}}{\sqrt{d}} / \sqrt{2} = \pm \frac{1}{\sqrt{d}}$
and direct computation shows $H_d^T H_d = I$

Note to compute $H_d u$, we may write

$$H_d \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} H_{d/2}(u_1 + u_2) \\ H_{d/2}(u_1 - u_2) \end{bmatrix}$$

So can proceed inductively. In each step we need to compute $u_1 + u_2, u_1 - u_2$ and there are $\log(d)$ steps. So total cost is $d \log(d)$.

We'll introduce randomness by letting D be a diagonal matrix with random sign $\varepsilon_i = \{-1, +1\}$ entries.

Set $R = HD$. Can check that R is also Hadamard.

Lemma: For any u set $v = HDu$. Then

$$P\left[\frac{\|v\|_\infty}{\|v\|_2} \geq \sqrt{\frac{2 \log(\frac{4d}{\delta})}{d}}\right] \leq \frac{\delta}{2}$$

Pf: Observe $\|v\|_2 = \|u\|_2$ and

$$v_i = \sum_j \varepsilon_j H_{ij} u_j$$

So by Hoeffding v_i is subgaussian with param $\sqrt{\sum_j H_{ij}^2 u_j^2} = \|u\|_2$. Therefore

$$P[|v_i| \geq \lambda \|u\|_2] \leq 2 \exp\left(-\frac{\lambda d}{2}\right) = \frac{\delta}{2^d}$$

Taking union bound over i completes the pt.

Finally putting the two lemmas together gives the theorem.

Thm (Fast JL Transform)

Define the matrix $\underbrace{X = L \cdot H \cdot D}_{\substack{\text{supersparse} \\ \text{Hadamard}}}$ $\underbrace{D}_{\substack{\text{random} \\ \text{diagonal}}}$

$$X = L \cdot H \cdot D$$

Then with probability $1 - \delta$, we have

$$1 - \delta \leq \frac{\|Xu - Xv\|_2}{\|u - v\|_2} \leq 1 + \epsilon \quad \forall u, v \in \mathbb{R}^n$$

provided

$$n \geq \frac{2 \log\left(\frac{4m^2}{\delta}\right) \log\left(\frac{4dm^2}{\delta}\right)}{\epsilon^2}.$$

Forming Xu requires $d \log(d) + n$ flops.

Note this n is worse than n from JL by a factor of $\log(dm)$.

Pf: For any u , with prob $1 - \frac{\delta}{2m^2}$ w.r.t. D we have

$$\textcircled{1} \quad \frac{\|HDu\|_\infty^2}{\|HDu\|_2^2} \leq \lambda = \frac{2\log\left(\frac{4dm^2}{\delta}\right)}{d}$$

Conditioned on this event E , with probability $p = 1 - 2\exp\left(-\frac{\epsilon^2 n}{d^2 \lambda^2}\right)$ we have

$$\textcircled{2} \quad \left| \underbrace{\|LHDu\|_2^2 - \|HDu\|_2^2}_{\|Xu\|_2^2} \right| \leq \epsilon \underbrace{\|HDu\|_2^2}_{\|u\|_2^2} \underbrace{\|u\|_2^2}_{\|u\|_2^2}$$

$$\text{Note } p = 1 - 2\exp\left(-\frac{\epsilon^2 n}{2\log\left(\frac{4dm^2}{\delta}\right)}\right) = 1 - \frac{\delta}{2m^2}$$

Let E be the event where $\textcircled{1}$ holds and F the event that $\textcircled{2}$ holds. Then $P[E \cap F] = P[F | E] \cdot P[E]$

$$\geq \left(1 - \frac{\delta}{2m^2}\right) \cdot \left(1 - \frac{\delta}{2m^2}\right)$$

$$\geq 1 - \delta/m^2$$

Take union bound over $u = x-y$ for $x, y \in \mathbb{R}$